Icon Design and Game App Adoption

Completed Research Paper

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Abstract

How do customers make selections from among millions of smartphone apps? In this study, we analyzed the relationship between icon attributes and choice of game apps. Based on the literature, 5 icon attributes were identified: active, balance, complexity, depth, and organic. 3 game types were selected: arcade, brain, and casual games. Explicit policy implications were exploited for icon design. For arcade games, icons should be active. For brain games, icons should be organic. For casual games, organic and depth are the preferred criteria for designs.

Keywords

Icon, logo, app, Wilcoxon, Probit

Introduction

Today's smartphones are full of apps – mini software applications designed to run on smartphones, tablet computers, and other mobile devices. Two prominent app markets are Android's Android Market (aka Google Play) and Apple's Apple Store. Since its opening on July 14, 2008, Apple Store has received 25 billion downloads as of March 5, 2012 (Apple Inc., 2012). Google Play reached this number on September 26, 2012 (Google Android Official Blog, 2012). Together these represent over 1 million apps according to unofficial statistics (mobiles.co.uk, 2012). The year 2011 was a watershed in the smartphone market; it was the first time smartphone shipments overtook those of client PCs (488 million versus 415 million) (Canalys, 2012). Our question is: Given millions of apps to choose from, how do customers make their selections?

Most of these apps are free. According to Androlib (Androlib, 2012), at the Android marketplace 67.5% of the apps are free. Gartner estimates that 89% of the apps at its App Store are free, and they expect that number to rise to 93% by 2016 (Gartner Newsroom, 2012).

For app developers, "free" is a strategy. Making the software free increases the user base, which is especially useful if the software demonstrates "network externality"; that is, the user's utility increases exponentially when more users share in the play. These developers make their profits by applying "InAppPurchase" (IAP). This profit model is popular among game apps users; simple use of the software is free, but players must pay to upgrade their weapons, subscribe to magazines/tutorials, or buy more points.

How can a single product attract attention in a sea of millions of "free" software apps? In our study, 159 of 208 survey respondents acknowledged that they chose apps based on their icons – the small graphical squares which deliver the messages the software apps are intended to deliver. The literature also demonstrates that logos, typefaces, package designs, and other exterior designs can affect customer loyalty, brand impression, and purchasing behavior (Henderson, Giese, & Cote, 2004; Machado, Vacas-de-Carvalho, Costa, & Lencastre, 2012; Orth & Malkewitz, 2008; Pham, Pallares-Venegas, & Teich, 2012; van der Lans et al., 2009). According to pattern recognition theory (Selfridge & Neisser, 1963), features such as attributes function as stimuli that provide a foundation that viewers can use to decode the meaning of the icons.

In their pivotal work, Henderson and Cote (1998) identified certain design principles for logos. Our study shifted the focus from "what makes good logos" to the causality between the adoption of apps and icon attributes. We wanted to explore which icon attributes improve the adoption of a given app category.

Games constitute 25.6% of app downloads (Android Developers Blog, 2011). Due to its significance, we will focus on this category. Among the many categories of games, the top 3 are arcade games, brain games, and casual games. According to the Android Developers Blog, these represent 79.07% of total game downloads. There is a huge gap between the weakest of the top 3 (casual) at 17.68% and the next in line (card games) at 7.31%. Thus, we focus on the 3 top categories.

Literature review

Research has identified the effectiveness of images (including icons, logos, and packages) in product recognition, corporate identification, marketing, brand impression creation, etc. (Henderson & Cote, 1998; Henderson, Giese, & Cote, 2004; Machado, Vacas-de-Carvalho, Costa, & Lencastre, 2012; Orth & Malkewitz, 2008; Pham, Pallares-Venegas, & Teich, 2012; van der Lans et al., 2009). Peters (1999, p. 41) recognized the importance of a visually strong logo: "Humans think visually. A picture is really worth a million words. And great brands have readily identifiable icons – just ask Nike or Apple or Shell – strong simple images that connect with customers."

However, there have been only a few recent published studies on the relationship between logos and the choice of products/services. Prominent among these, Henderson and Cote (1998) and Henderson, Giese, and Cote (2004) proposed guidelines for good design of logos and typefaces. Orth and Malkewitz (2008) developed a holistic package design that creates a better brand impression for consumers. Pham, Pallares-Venegas, and Teich (2012) delineated relationships among logos, storytelling, and customer loyalty. Pittard, Ewing, and Jevons (Pittard, Ewing, & Jevons, 2007) examined consumer responses to logo designs. Machado, Vacas-de-Carvalho, Costa, and Lencastre (2012) and Hagtvedt (Hagtvedt, 2011) analyzed the effect of logo designs in specific circumstances. Although these studies have paved the way for logo research in the field of management, they provide little guidance for choosing the best logo design for a particular product/service. We believe this guidance is important to have, especially when customers must choose from a large number of logos. As noted by Pham et al. (2012), logos tell stories. But if the logo doesn't catch the customer's eye, the story has no place to start. Due to the proliferation of software packages, a tempting research question is how to apply these logo studies to research on icons.

In Section 0, we summarize the pattern recognition theory, which explains the process by which viewers recognize icons. In Section 0, we review Henderson and Cote (1998)'s logo attribute theory and other relevant research. We then describe how we applied these principles in our icon-app adoption research.

Pattern recognition theory

The first issue we need to address is why icons or logos can become emblems that represent meanings. Pattern recognition theory can help us understand this. The theory describes a process for recognizing a set of stimuli arranged in a pattern that is characteristic for that set of stimuli. The process includes the successive collection, encoding, decoding, and storage of the characteristics in memory. The primary theory serves as an umbrella for 3 competing secondary theories that are purported to explain the pattern recognition process (Selfridge & Neisser, 1963).

1. Template matching theory

Selfridge and Neisser (1963) propose that human beings store templates in long term memory. These templates represent our past experiences and learning. When a new logo is received by the sensory system, the stored templates are retrieved and compared to the logo. The logo is considered to be successfully recognized when it is matched to the template.

2. Prototype matching theory

A prototype is the most representative characteristic of a particular object. The object is recognized by the sensory system when a match is found with a sufficiently similar prototype.

3. Feature-discrimination theory

According to this theory, the sensory system breaks down the incoming stimuli into its features and then processes them. Object recognition involves re-assembling the features to determine what the object is.

We believe feature discrimination is the best theory for our study. For template matching, a template must be established in the sensory system, but the app market, because of its novelty, may present many unseen patterns for which it is difficult to find templates for comparison. For prototype matching, the large variety of apps could make it difficult to generate a prototype. In contrast to these 2 theories, feature-discrimination theory does not require *ex ante* templates or prototypes; people simply recognize patterns from the features that make up the image.

Icon attributes

Based on Henderson and Cote (1998) and Nemett (Nemett, 1992), we distinguished 5 different attributes of icons and predicted which of these would draw the most attention for which game categories.

(1) Organic

According to Henderson and Cote (1998), "Organic designs are those that are made up of natural shapes such as irregular curves. Graphic design literature suggests that organic designs are more meaningful (Dondis, 1973)" (see

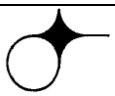
Attribute	High	Low
Organic		
Balance		
Complexity		
Active		
Depth		

Table 1).

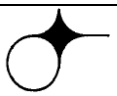
Attribute	High	Low
Organic		
Balance		
Complexity		
Active		
Depth		

Table 1 Attributes of logo designs

(2) Balance

According to Henderson and Cote (1998), "Balance captures the notion that there is a center of suspension between two weights or portions of the design. Graphics design literature has suggested that imbalance is more upsetting to viewers (Dondis, 1973)."

(3) Complexity

According to Henderson and Cote (1998), "Complexity can arise from many different design features such as irregularity in the arrangement of elements, increases in the number of elements, heterogeneity in the nature of elements, and how ornate the design is (Berlyne, 1971; Schmitt, Simonson, & Marcus, 1995)."

(4) Active

Henderson and Cote (1998) defined active designs as "those that give the impression of motion or flow. This flow is the basis for the design notion of rhythm (Bevlin, 1989)."

(5) Depth

According to Henderson and Cote (1998), depth "gives the appearance of perspective or a three-dimensional design."

Henderson and Cote (1998) also described symmetric and representative designs. Symmetric designs are those that "appear as reflections along one or more axis. That is, the elements on one side of the axis are identical to the elements on the other side." A "representative design and its opposite endpoint, abstract, capture the degree of realism in a design." "Symmetric designs are normally considered balanced." In the same vein, they cite other researchers (Block, 1969; Clark, 1988; Durgee & Stuart, 1987; John Peter, 1989; Keller, 1993; Kropp. H. Richard, Warren A. French, and Jimmy E. Hilliard, 1990; Masten, 1988; Siegel, 1989; Vartorella, 1990; Yeung, 1988), claiming that the "logo strategy literature frequently suggests using representative logos." We thus incorporate the symmetric design as a subset of the balance design and ensure that all our logos have the representative design feature.

Research methodology and procedure

To evaluate how icon attributes affect the choice of apps, we designated 15 icons for each game type, with each attribute represented by 3 icons. To guarantee that the icons represent the attributes well, we first interviewed domain experts to understand the design principles for each of the 3 game types – arcade, brain, and casual. An Arcade game involves avatars whose goal is to survive. A brain game requires players to think; it is usually educational. A casual game is targeted at or used by a mass audience of casual gamers. It is typically distinguished by its simple rules, lack of commitment, and lack of requirement of special skills. We designed 3 virtual games specifically for our study: ML-Run (arcade), ML-Square (brain), and ML-Farm (casual).

Then, 9 designers were invited to design the icons for all the games. Initially, 120 icons were drawn, representing 40 icons for each game or 8 icons for each game/attribute combination. Because all the icons were designed exclusively for this experiment, there is little chance that the participants had ever seen them.

The next step was to assure that the icons represent the attributes well. This is said to happen if and only if a significant number of respondents agree that the representation is valid. To achieve this objective, we needed to set a threshold value. A value of 6 means that the icon can be considered to represent the attribute only if 60% of the respondents agree that this is so. The Delphi method (Dalkey & Helmer, 1963) was employed to determine the appropriate threshold value. 7 experts, including 2 professors, 2 designers, and 3 MIS professionals, participated in the Delphi session. A web-based GDSS tool, TeamSpirit, was employed (Chen, Liou, Wang, Fan, & Chi, 2007) for the session. The experts started brainstorming in the first round; the main topic was, "What makes an icon a good representation of an attribute?" In the second round, the discussion was routed to the determination of "reasonable threshold values for an icon to represent an attribute well." The proposed values were 6.0, 7.5, and 9.0. In the last round, the participants voted for the final threshold value of 7.5.

Next, all 120 icons were presented to 50 pilot study participants. They observed each one and selected which attribute or attributes it represented. An icon was considered well represented if 38 (50*0.75=37.5) or more participants identified 1 and only 1 attribute. An icon was labeled as over-represented if it was considered by 75% or more of the participants to represent 2 or more attributes. It was labeled as under-represented if it failed to represent any attribute. All over- or under-represented icons were discarded. The 3 best well-represented icons then were chosen to represent each game/attribute combination. However, for organic, depth, and complexity (arcade games) and for active and depth (casual games), fewer than 3 icons could be found initially. In these cases, the designers drew new icons until every attribute/game combination had the required 3 icons.

The above procedure guarantees the reliability and validity of the icons' attribute representations. It assures that each set of 3 icons represents one and only one attribute. Similar icons are joined in single sets. Thus, reliability, convergent validity, and discriminant validity are all achieved.

	Organic	Balance	Active	Complexity	Depth
Arcade					
					
					

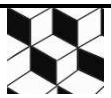
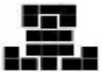
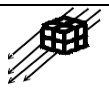
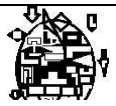
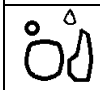
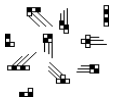
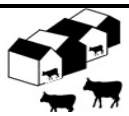
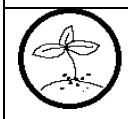
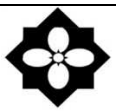
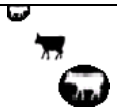
Brain					
					
					
Casual					
					
					

Table 2 shows the icons selected for the experiment.

	Organic	Balance	Active	Complexity	Depth
Arcade					
					
Brain					
Casual					

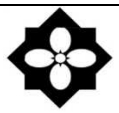
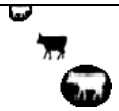
					
					

Table 2 Icons used for the experiment

During the main test, each participant was given an imitation smartphone with cardboard icons attached to its screen and covered by glass. Both the phone and icons were the same size as their real counterparts. To avoid fatigue (van der Lans et al., 2009), each participant was given only 1 of the 3 icons for each game/attribute combination. The participant was then asked to rank the 5 icons for each game category based on their preferences: a rank of 1 represented the greatest desire to download the game app when observed and 5 represented the least.

The experiment was conducted in Taiwan near the university campuses we believed had the highest likelihood of many smartphone users. Those who had previously downloaded apps with smartphones were asked to participate. The experimenter gave them the instructions and recorded their answers. The number of valid questionnaires was 208.

Sample description and data analysis

The survey we used has 3 parts. Part 1 solicits demographic information. Part 2 gives respondents the chance to express their reason for downloading apps. Part 3 is the actual test, in which respondents rank the icons according to the likelihood they will download the app that the icon represents.

	Category	Sample size	Percentage
Gender	Male	139	66.82%
	Female	69	33.18%
Age	≦ 20	39	18.75%
	21-25	62	29.81%
	26-30	49	23.56%
	31-40	38	18.27%
	> 40	21	10.10%
Education	Postgraduate	94	45.19%
	Undergraduate	112	53.85%
	High school	2	0.96%
Profession	Student	120	57.69%
	Non-Student	88	42.31%
# of downloads in	< 5	75	36.06%
	6-15	64	30.77%

the past year	16-25	49	23.56%
	> 25	20	9.62%

Table 3 shows the characteristics of our sample.

	Category	Sample size	Percentage
Gender	Male	139	66.82%
	Female	69	33.18%
Age	≦ 20	39	18.75%
	21-25	62	29.81%
	26-30	49	23.56%
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	Undergraduate	112	53.85%
	High school	2	0.96%
Profession	Student	120	57.69%
	Non-Student	88	42.31%
# of downloads in the past year	< 5	75	36.06%
	6-15	64	30.77%
	16-25	49	23.56%
	> 25	20	9.62%

Table 3 Sample description

Part 2 assured us that the participants chose apps mainly because of the icons. Of the 208 respondents, 179 agreed that they downloaded apps based on icon designs. Although 168 participants based their download decisions on app ratings, 86 agreed that for many apps the ratings were insufficient or there were no ratings at all. 40, 35, or 27 participants chose icon colors, app names, or companies as their decision criteria respectively. The survey indicated that colors, app names, or companies are not an important factor.

Using the Friedman test on the 5 attributes selected by each participant, we found that some attributes were ranked significantly higher ($p < 0.01$) than others for each of the 3 games (see

	Arcade	Brain	Casual
Sample	208	208	208
χ^2	129.28	70.01	108.47
Degrees of Freedom	4	4	4
asymptotic significance	< .001	< .001	< .001

Table 4 Friedman test). We then conducted post-hoc Wilcoxon signed rank tests (see

Arcade										
	A-B	A-C	A-D	A-E	B-C	B-D	B-E	C-D	C-E	D-E
Z test	-7.136[b]	-8.444[b]	-9.551[b]	-7.885[b]	-1.998[b]	-.812[b]	-.219[a]	-1.313[a]	-2.242[a]	-1.051[a]
asymptotic significance (2-sided)	< .001	< .001	< .001	< .001	.046	.417	.826	.189	.025	.293
Brain										
	A-B	A-C	A-D	A-E	B-C	B-D	B-E	C-D	C-E	D-E
Z test	-1.549[b]	-1.621[b]	-.682[a]	-6.295[a]	-.211[b]	-2.710[a]	-6.575[a]	-2.293[a]	-6.181[a]	-4.502[a]
asymptotic significance (2-sided)	.121	.105	.495	< .001	.833	.007	< .001	.022	< .001	< .001
Casual										
	A-B	A-C	A-D	A-E	B-C	B-D	B-E	C-D	C-E	D-E
Z test	-2.354[b]	-.918[b]	-6.536[a]	-5.154[a]	-1.656[a]	-7.551[a]	-6.503[a]	-6.673[a]	-4.871[a]	-2.241[b]
asymptotic significance (2-sided)	.019	.358	< .001	< .001	.098	< .001	< .001	< .001	< .001	.025
a. negative rank b. positive rank (A: Active, B: Balance, C: Complexity, D:Depth, E:Organic)										

Table 5).

	Arcade	Brain	Casual
Sample	208	208	208
χ^2	129.28	70.01	108.47
Degrees of Freedom	4	4	4
asymptotic significance	< .001	< .001	< .001

Table 4 Friedman test

Arcade										
	A-B	A-C	A-D	A-E	B-C	B-D	B-E	C-D	C-E	D-E
Z test	-7.136[b]	-8.444[b]	-9.551[b]	-7.885[b]	-1.998[b]	-.812[b]	-.219[a]	-1.313[a]	-2.242[a]	-1.051[a]
asymptotic significance (2-sided)	< .001	< .001	< .001	< .001	.046	.417	.826	.189	.025	.293
Brain										
	A-B	A-C	A-D	A-E	B-C	B-D	B-E	C-D	C-E	D-E
Z test	-1.549[b]	-1.621[b]	-.682[a]	-6.295[a]	-.211[b]	-2.710[a]	-6.575[a]	-2.293[a]	-6.181[a]	-4.502[a]
asymptotic significance (2-sided)	.121	.105	.495	< .001	.833	.007	< .001	.022	< .001	< .001
Casual										

	A-B	A-C	A-D	A-E	B-C	B-D	B-E	C-D	C-E	D-E
Z test	-2.354[b]	-.918[b]	-6.536[a]	-5.154[a]	-1.656[a]	-7.551[a]	-6.503[a]	-6.673[a]	-4.871[a]	-2.241[b]
asymptotic significance (2-sided)	.019	.358	< .001	< .001	.098	< .001	< .001	< .001	< .001	.025
a. negative rank b. positive rank (A: Active, B: Balance, C: Complexity, D:Depth, E:Organic)										

Table 5 Wilcoxon signed rank test for games

The results show that for arcade games the active attribute is the first choice, followed by organic, balance, depth, and complexity. The rank order for brain games is organic, depth, active, balance, and complexity, and the rank order for casual games is depth, organic, active, complexity, and balance.

The results of the Wilcoxon tests allow us to further analyze the impact of the demographic variables on the rankings of attributes. We need to answer two questions. First, do demographic variables have an effect across all respondents on the ranking of a specific attribute for each type of game? For example, do males consistently rank the active attribute of arcade games higher than females do? An ordered probit was employed, and the regression of gender on the ranking of the active attribute for arcade games is as follows:

$$y_i = \alpha_0 + \alpha_1 x_{1i} \qquad (1)$$

where y_i is the ranking (from 1 to 5) that respondent i assigned to the active attribute for the arcade games and x_{1i} is i's gender. x_{1i} was coded 1 for males and 0 for females. For example, y_i = 4 and x_{1i} = 1 means that a male respondent (x_{1i} = 1) ranked the active attribute as the second highest (y_i = 4) for arcade game.

We followed the same convention for the other demographic variables and the other two game types. After conducting the ordered probit regressions using SPSS and verifying the results using Stata, we found no impact of the demographic variables gender, age, education, profession, and number of downloads in the past year on the rankings of the active attributes for arcade games. We applied the same technique to other attributes for other games and found no impact of the demographic variables on the rankings of any of the attributes for any game.

Second, do demographic variables affect the rank order generally for each type of game across all respondents? For example, to assess if there is a gender difference in the general rank order for arcade games, we apply the following formula:

$$y_{ij} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2j} \qquad (2)$$

where y_{ij} is the *specific* ranking that respondent i assigns to attribute j, x_{1i} is i's gender, and x_{2j} is the *overall* rank order (assigned by all respondents) of the j^{th} attribute for arcade games. This overall rank order was determined by a Wilcoxon test. For arcade games, x_{2j} = 5 when the attribute is active, x_{2j} = 4 when it is organic, x_{2j} = 3 when it is balance, x_{2j} = 2 when it is depth, and x_{2j} = 1 when it is complexity. Rank number 1 is the highest and was thus given a score of 5. For example, y_{ij} = 4, x_{1i} = 1, and x_{2j} = 2 means that a male respondent (x_{1i} = 1) ranked the balance attribute (x_{2j} = 2) as the second highest (y_{ij} = 4) for arcade games. Adding x_{2j} to the equation is both necessary and beneficial. Without it, gender (x_{1i}) and attribute rank (y_{ij}) cannot be correlated. On the other hand, we suspected that the relationship between y_{ij} and x_{2j} would prove to be asymptotic instead of linear, so we also tested the following regression:

$$y_{ij} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2j}^2 \qquad (3)$$

Equation $y_{ij} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2j}^2$ (3) has greater explanatory power than Equation $y_{ij} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2j}$ (2) (adjusting R^2 are 0.1228 and 0.1052 respectively), demonstrating that the relationship is asymptotic. We found no effect of demographic variables on attribute rankings with either equation. The tests with brain games and casual games led to the same conclusions.

We also tested x_{1i} and x_{2j} for multicollinearity using ordinary regression and found it not to be significant. There also was no significant heteroscedasticity or autocorrelation, because the error terms for probits or ordered probits are always standard normal.

Findings and conclusions

Contribution

One of the basic principles that separates this study from previous studies is our assumption that different application types require different icon designs; previous research emphasized what makes good logo design. Although there are universal rules that govern what good designs are, there are also specific rules for determining what designs should be employed in what situations. This study proved that arcade, brain, and casual games each require different icon designs to attract users. The Wilcoxon tests have clear implications for business.

Arcade										
	A-B	A-C	A-D	A-E	B-C	B-D	B-E	C-D	C-E	D-E
Z test	-7.136[b]	-8.444[b]	-9.551[b]	-7.885[b]	-1.998[b]	-.812[b]	-.219[a]	-1.313[a]	-2.242[a]	-1.051[a]
asymptotic significance (2-sided)	< .001	< .001	< .001	< .001	.046	.417	.826	.189	.025	.293
Brain										
	A-B	A-C	A-D	A-E	B-C	B-D	B-E	C-D	C-E	D-E
Z test	-1.549[b]	-1.621[b]	-.682[a]	-6.295[a]	-.211[b]	-2.710[a]	-6.575[a]	-2.293[a]	-6.181[a]	-4.502[a]
asymptotic significance (2-sided)	.121	.105	.495	< .001	.833	.007	< .001	.022	< .001	< .001
Casual										
	A-B	A-C	A-D	A-E	B-C	B-D	B-E	C-D	C-E	D-E
Z test	-2.354[b]	-.918[b]	-6.536[a]	-5.154[a]	-1.656[a]	-7.551[a]	-6.503[a]	-6.673[a]	-4.871[a]	-2.241[b]
asymptotic significance (2-sided)	.019	.358	< .001	< .001	.098	< .001	< .001	< .001	< .001	.025
a. negative rank b. positive rank (A: Active, B: Balance, C: Complexity, D:Depth, E:Organic)										

Table 5 shows that the active attribute (labeled A) is clearly ranked higher than the other design attributes for arcade games; that is, icons with the active attribute attract more people to download arcade games than those with other attributes. The table also reveals that complexity is ranked in general lower than the other attributes; this means that complexity should be avoided when designing game icons. Our post-survey interviews revealed that the active attribute implies dynamism and a sense of sport, and this is why icons with this attribute was chosen so frequently. Complexity gave users the feeling that the games are difficult and that they could not achieve their mission. This makes sense because arcade games often involve competition and survival is the goal.

For brain games, the organic attribute (Labeled E) was the first choice. This makes sense, because "organic designs are more meaningful" (Henderson & Cote, 1998); that is, organic designs inspire the inquisitive mind, and such inspiration motivates users to try brain games. The depth attribute came in second but is not statistically superior to the active attribute, which came in third.

For casual games, the depth attribute was the first design choice, with the organic attribute coming in second. The balance attribute ranked lowest, and its inferiority to complexity was suggestively significant

($p < 0.10$). The post-survey interviewees revealed that the depth attribute provided a comfortable visual effect and relaxed them.

As we can see, each game category had its own first choice. This proves that specific rules are important. Although not always statistically significant, the first choice for casual games – depth – turned out to be a bad choice for arcade games. This means that if managers wrongly choose their icon attributes, they will get opposite results in different games. Similarly, active was the first choice for arcade games, but its ranking was mediocre in the other 2 game categories. The same situation applies to the first choice for casual games - depth.

The above conclusions are the main contribution of our study. However, the rankings cannot be grasped intuitively and statistical analysis was required. We used the Friedman test, the Wilcoxon signed rank test, and ordered probit for our specific data type; this practice is not common in the MIS field.

The fact that the relationship between rankings and attributes (Equation $y_{ij} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2j}$ (2 and $y_{ij} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2j}^2$ (3) is asymptotic is insightful. It shows that customers usually have clear icon preferences on a certain type of games for the top one or two choices, but the preference among the other attributes are less distinctive. This is true for all the three game types. The Wilcoxon signed rank test (

Arcade										
	A-B	A-C	A-D	A-E	B-C	B-D	B-E	C-D	C-E	D-E
Z test	-7.136[b]	-8.444[b]	-9.551[b]	-7.885[b]	-1.998[b]	-.812[b]	-.219[a]	-1.313[a]	-2.242[a]	-1.051[a]
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Brain										
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asymptotic significance (2-sided)	.019	.358	< .001	< .001	.098	< .001	< .001	< .001	< .001	.025
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Table 5) also shows this message. Take arcade games as an example. The active attribute is clearly the top choice but the users do not differentiate other four attributes.

Practical implications

We provide the following practical suggestions, which are similar to those of van der Lans et. al. (2009) and (Kohli, Suri, & Thakor, 2002) :

1. App developers should realize that icons really do matter. We need to pay attention to our conclusions from Section 0.
2. An optimal design choice for one type of game type might be a bad design choice for another type of game.

3. Developers should communicate with icon designers about design attributes. They are a short vocabulary for design communication.
4. In cases where our results are highly significant statistically, developers should stick to icons that we found are good for a particular game type and avoid icons that consumers are unlikely to download.

Developers should be systematic and objective and allow designers to modify the icons for individual game types. Users should follow our suggestions rather than rely solely on the opinion of a particular icon designer.

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